Spatial Patterns for Crime Spots

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Abstract

Research shows that crime patterns are highly dependent on the environment and the presence of possible guardianship. Recent studies focus on the effects of various explanatory variables on spatial crime analysis, using environmental criminology as a basis. This study considers the notion of place in defining spatial patterns for hot and cold crime spots in the city of Manchester, UK. Global and local spatial regression models are employed to determine statistically significant relationships between crime types and spatial features. Results show high R^2 for hotspots, indicating a representative spatial pattern; however, additional information is needed for coldspots.
Keywords: spatial crime patterns; criminogenic factors; place.

1 Introduction

The occurrence of crime within a city fluctuates from place to place. There are regions that exhibit high crime rates (hotspots); others feature a significant drop on crimes (coldspots), whereas, areas in between reveal a moderate criminal behaviour. The varying crime density implies that some locations favour the crime activity more than others. This work investigates why different regions allow disparate crime rates. Based on the assumption that physical features can affect the occurrence of crime, we proceed to the extraction of patterns that describe the spatial composition of crime spots. Particularly, this study examines the significance of physical entities in report to crime occurrences by investigating crime spots and consulting criminology-related literature. Then, explanatory composition patterns are proposed that describe the constitution of the corresponding crime spots.

According to crime pattern theory (Brantingham and Brantingham 1981), crimes are not random events. There are factors, known as crime attractors or generators (Brantingham and Brantingham 1995) that boost the crime occurrences in certain areas (e.g. crowded or isolated places). Findings like the former tackle the environmental criminology to extract and analyse spatiotemporal criminal patterns in terms of the potential impact they receive from external variables, such as spatial features, socioeconomic and demographic elements, and so forth.

Factors that influence crime rates are not universal; they may affect differently particular crime types. Furthermore, some have their influence modified by additional parameters, such as country type, urban or rural level, economical status and so on (Ratcliffe 2012). This encourages the extraction and analysis of crime patterns associated with different locations (Malleson and Andresen 2015).

The analysis of crime hotspots is one of the most prevalent methods for explaining and predicting crime activity. There is a plethora of approaches that deal with the extraction of spatial crime patterns based on crime hotspots for both aggregated and disaggregated crime types (Eck et al. 2005, Chainey et al. 2008). For instance, researchers found criminogenic spatial influence of businesses such as bars and liquor stores on street robberies (Bernasco and Block 2011); whereas, social, cultural and age related factors found to be influential for antisocial behaviour (Moffitt 1993, Rodger 2012). Most of the approaches introduce and describe each hotspot as an individually bounded area containing spatial features. However, a place is vulnerable to crime risk because of the spatial influence of criminogenic features throughout the landscape (Caplan and Kennedy 2011).

This study advances state of the art by analysing crime hotspots collectively and also extending the analysis to coldspots, which to the best of our knowledge are not always addressed in literature. The spatial patterns are constructed by the exhaustive analysis of crime spots and consider the latter as a system that adheres to certain constructive guidelines. This is addressed by adapting the notion of place and assuming that a crime spot is a properly designed place that attracts high or low criminal behaviour.

Place is a human invention to describe space (Curry 1996); “place is space infused with human meaning” (Tuan 1977). There are several works aiming to formalize the concept of place and they vary according to the direction of focus: space to meaning or meaning to space. Each approach emphasizes on different aspects of meaning; they range from semantic infusion of space, such as qualitative space (Frank, 1996), to sophisticated models, such as association of people's actions with affordances (Jordan et al. 1998). A more recent approach is the function-based model of place (Papadakis el al. 2016), which focuses on functional space. It is based on the assumption that places serve human intentionality by providing functions, which in return are enabled or disabled based on the spatial configuration, henceforth composition, of the constituents of the place.

For the purposes of this work we opted to rely on the latter model. We utilize the constructive nature of place, that is, the spatial features and external variables that affect crime rates in our study, with the support of functions, that is, the capability or impotence of criminal behaviour in our study. The remainder of this paper is organized as follows. First we introduce a place-driven description of crime spots, followed by the introduction and formalization of a place-based spatial pattern. Then we emphasize on the extraction of patterns for two types of crime. The next section focuses on the discussion of the results, followed by concluding remarks and future work.

2 Methodology

The composition of place determines how various spatial features along with their properties enable certain functions. Assuming that crime hotspots are places with high, low or neutral crime rates, we focus on introducing the significant spatial features that justify these crime occurrences.

We introduce a place-based pattern of crime spots that includes comprised physical entities, along with some in-between associations. More specifically, the composition pattern of crime spot is defined as follows:

- Significant features (henceforth SF)
  - All the features that affect the occurrence of crimes
- Correlation
  - Average proportion of the occurrence between paired SF
- Distribution
  - Average Moran's Index of the SF

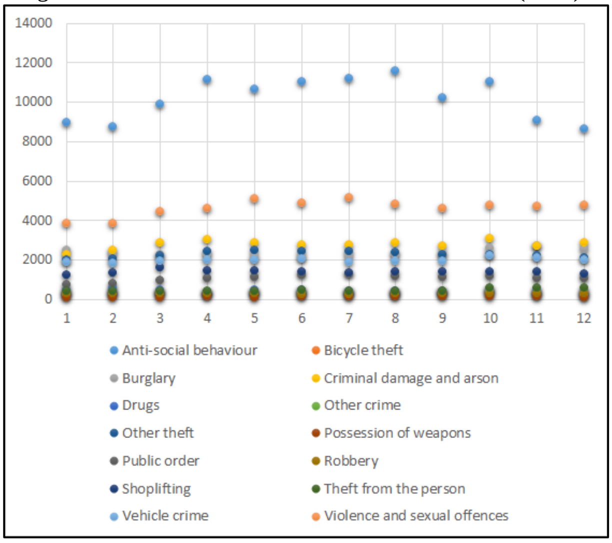
In this study, we extract composition patterns of hot and cold spot areas in Manchester, United Kingdom. The spatial units, which bound the crime spots, are represented by the Lower Super Output Areas (LSOA) in the city of Manchester, including 282 polygons.

2.1 Data

The data used include aggregated monthly crime data from police.co.uk for 2015, analysed for Manchester City Council boundary as a part of Greater Manchester. Our study includes the two most intense crime types in Greater Manchester (Figure 1), namely Anti-social behaviour (henceforth Antisocial crime) and Violence and Sexual offences (henceforth Violent crime). All the analyses are executed using British National Grid Projection (EPSG 27700).

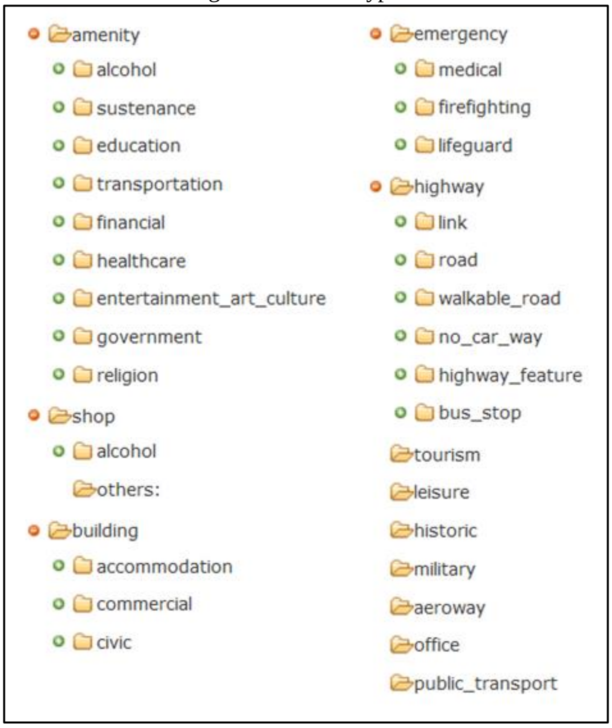
The spatial features that construct the crime patterns are extracted from the freely available information provided by Openstreetmap. The types of spatial features follow a hierarchical organization that is extracted by combining the data organization provided in the Openstreetmap portal (https://wiki.openstreetmap.org/wiki/Category:Keys) and the importance of some features based on hotspot analysis literature. Using the notation from the tag-system of Openstreetmap, Figure 2 illustrates the organization of the types of feature.

Figure 1: Crime occurrences in Greater Manchester (2015).



Source: www.police.co.uk

Figure 2: Feature types.



Lastly, we utilized additional meta-data including residential population from Census 2011 and house prices from the UK open data portal (median price paid value for 2015).

2.2 Preprocessing

The creation of composition patterns is conducted for every crime type and it is initiated with the analysis of the spatial features contained in every crime spot. Particularly, for every type of crime spot, among others, the following fields are calculated: feature type counts, average frequency of occurrence per feature type and average proportion of occurrences between exhaustive pairs of feature types. The significant spatial features for each type of crime spot are extracted by applying statistical analysis on the aforementioned data. Afterwards, representative composition patterns are introduced by correlating the results of the statistical analysis with the previously calculated frequencies.

2.3 Crime Spots and Singificant Features

The crime data contained in the LSOA polygons are aggregated and fed into the Optimized Hot Spot analysis algorithm, which is applied for both the Antisocial and Violent crimes. This spatial tool identifies statistically significant clusters of high values (hotspots) and low values (coldspots) using the Getis-Ord Gi* algorithm (Ord and Getis 1995). Furthermore, it evaluates the main characteristics of the dataset by checking for spatial dependence through multiple testing. If necessary, it provides corrections by using the False Discovery Rate (FDR) correction method. We accept hotspots that are significant at 99%, 95% and 90% confidence level; similar assumptions are followed for the coldspots. The crime spots introduce four bounded entities, which are to be used for the extraction of crime patterns: those created by the hot and cold spot polygons for both Antisocial and Violent crimes.

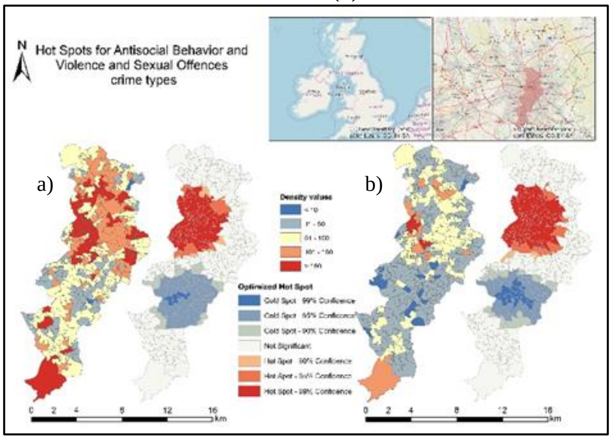
Using the data described above, three regression methods are employed to estimate significant explanatory variables for crime occurrences: (1) Exploratory regression, showing the best combinations of the independent variables; (2) Spatial Lag Models - Maximum likelihood estimation, a global model showing statistically significant independent variables; (3) Geographically Weighted Regression (GWR), a local model determining goodness of fit per spatial unit of analysis.

3 Results and Discussion

City of Manchester has a central business area with high concentration of both crime attractors and crime generators, such as busy shops, entertainment amenities, and transportation nods. The density maps (shown in Figure 3) outline the intensity for both Antisocial and Violent crimes; however the high dispersion of the results makes it difficult to identify places with significant high or low crime attraction.

Utilizing the Optimized Hot Spot tool, we identify the hot and coldspots for each crime type. Grouping crime spots of the same type introduces unified regions of high or low criminal activity as it is shown in Figure 3. These primal findings are justified by the existence of the city center at the center-north part of the city (crime attractor) and mainly residential areas at the center-south part of the city.

Figure 3: Crime density (left) and hotspot analysis (right) for Antisocial Behavior (a), and Violence and Sexual Offences (b).



After defining the places with significantly high and low crime activity we proceed to the design of composition patterns. Exploratory Regression is applied in ArcGIS 10.5.1 in order to identify the most influential variables for each type of crime spot. The combinations are calculated using the OLS regression. In the models, we included a Spatial Weights Matrix created using Contiguity-Edges-Corners for the concept of spatial relationships and the Euclidean Distance method. Table 1 illustrates the most influential variables, which are those being significant in more than 50% of the tested models (Table 1).

Table 1. Summary of feature significance in all the exploratory regression models

		Antisocial (%)		Violent (%)	
		Hot Spot	Cold Spot	Hot Spot	Cold Spot
Models for categories	Amenity	100	84,16	100	
	Office	69,99		78,68	
	Emergency	54,07		50,14	
	Leisure	66,42		51,45	
	Tourism	66,51	63,52	54,16	
	Highway	96,16		100	
	Population		65,48	56,54	100
	House price		83,45		77,94
Models for subcategories	Alcohol shop	55,41			
	Financial	62,85		71,74	
	Alcohol amenity	100		89,08	
	Government	78,09		100	
	Sustenance	100	75,33	100	
	Art-culture	66,6			
	Healthcare	60,72			
	Transportation	79,05		89,76	
	Education	70,65		93,01	
	Medical	60,5		76,36	
	Bus stops	99,98		100	
	Population		79,31		99,72
	House price		90,62		81,2

The results indicate that features are highly significant for the hotspots of Antisocial and Violent crimes, while residential population has negligible influence over any type of crime.

This is supported by (Goldsmith et al. 2000), which states that relatively few people live in city centers. On the contrary, residential population and house prices are significant for all coldspots, while, most of the features insignificant. Amenities and tourism (in a broader view) and sustenance (in a finer categorization) features are some notable exceptions that affect the coldspots of Antisocial crimes.

The next step applies the Spatial Lag Maximum Likelihood approach to the variables of Table 1. This method is selected instead of Ordinary Least Squares (OLS), because it deals with the spatial dependence between variables and its results are shown in Table 2. Note that categories and subcategories are analyzed in two separate models due to multicollinearity.

General category features like tourism and highways are significant for the hotspots of both crime types, whereas amenities and offices affect only the Violent crimes. On the other hand, subcategory features like financial, governmental, sustenance, and bus stops facilities are important for all the hotspots. Alcohol shops seem to affect Antisocial crimes, whereas and alcohol amenities and transportation are important for Violent crimes. This is consistent with prior studies (Webb et al. 1996, Measham and Brain 2005).

Similarly to the exploratory regression, the residential population has negligible influence for all types of crime. Although the coldspots conform to the results of the previous method, there is a notable contradiction. The residential population is insignificant for the coldspots of Antisocial crimes. This further supports the argument that population can be a misleading factor. Finally, the house prices are significant for all coldspots, similarly to the explanatory regression results, which is justified by (Gibbons and Machin 2008).

Table 2. Results of Spatial Lag models

		Antisocial		Violent	
		Hot Spot	Cold Spot	Hot Spot	Cold Spot
Models for categories	Amenity	5,968	2,4148***	1,8598***	
	Office	-3,2427		6,9657°	
	Emergency	14,2932		5,2873	
	Leisure	19,4594		5,0593	
	Tourism	11,3593*	42,2509***	4,8544°	
	Highway	4,0784**		2,5982***	
	Population		0,0142	0,01854**	0,0321***
	House price		-0,0002***		-0,0001**
Models for subcategories	Alcohol shop	82,4664**			
	Financial	-15,241**		-6,1376**	
	Alcohol amenit	12,3356		3,7167***	
	Government	58,2589**		40,4251***	
	Sustenance	6,4693***	4,5684**	2,9214***	
	Art-culture	5,5677			
	Healthcare	11,2234			
	Transportation	5,3662		3,4061**	
	Education	4,6783		11,792	
	Medical	-20,1079		-1,0144	
	Bus stops	6,0764***		2,7575***	
	Population		0,0286		0,0321***
	House price		-0,0001**		-0,0001**

Note: °p ≤ 0.09. *p ≤ 0.05. ** p ≤ 0.01. *** p ≤ 0.001.

Table 3 shows the R^2 values that indicate how well the significant variables represent the crime spots. For both types of crime the hotspot models have an $R^2 > 0.90$, which means that the significant variables are an accurate description of crime rates. On the contrary, coldspot models are inaccurate, probably because of inadequate representative variables.

Table 3. R^2, Log Likelihood and AIC measures of Spatial Lag models

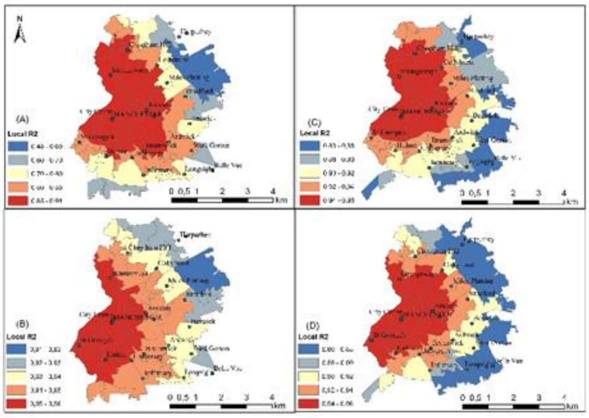
		Antisocial		Violent	
		Hot Spot	Cold Spot	Hot Spot	Cold Spot
Models for categori	R²	0,938888	0,356761	0,927223	0,310309
	Loglikelihood	-349,174	-305,488	-328,432	-262,809
	AIC	714,349	622,976	674,864	533,618
Models for subcate	R²	0,960336	0,263971	0,950839	0,310309
	Loglikelihood	-336,015	-309,684	-315,245	-262,809
	AIC	698,03	629,367	650,49	533,618

Table 3 offers a global overview of how well the crime occurrences are represented by the model. For a finer analysis we apply local testing using GWR (Brunsdon et al. 1996) models on the statistically significant features defined before. Table 4 indicates lower R^2 values for the Antisocial hotspots in the case of general category features. This may be due to some hotspots being less represented by those general spatial features. Figure 4 illustrates how well the significant variables describe the crime activity moving from higher values on the west to lower ones on the east. This is justified by the fact that the west side includes crime attractors, such as the city center, called by the UK government the counterfeit capital (Abbit 2017).

Table 4. R^2, R^2 adjusted and AIC measures of GWR models

		Antisocial		Violent	
		Hot Spot	Cold Spot	Hot Spot	Cold Spot
Models for categori	R²	0,8795	0,4475	0,9434	0,4156
	R² Adj.	0,8488	0,3544	0,9250	0,3377
	AIC	766,4518	621,7311	676,9966	531,7773
Models for subcate	R²	0,9525	0,4796	0,9527	0,4156
	R² Adj.	0,9399	0,3409	0,9334	0,3377
	AIC	712,9565	625,8633	671,8312	531,7773

Figure 4. R^2 measure for GWR hot spot models



Note: (A) Antisocial - feature categories; (B) Antisocial - feature subcategories; (C) Violent - feature categories; (D) Violent - feature subcategories

According to the above, we introduce a spatial pattern that describes the hotspots of both crime types. This pattern is composed by those variables that imply the highest accuracy, which are the most significant subcategory features. Initially, a distribution analysis is conducted for the significant subcategories on those LSOA polygons that contain at least 30 instances of them. This includes four polygons with sustenance amenities, two polygons with bus stops and two polygons with alcohol amenities. The results of the Spatial Autocorrelation (Moran's I) show a clustered pattern for all three spatial features. The spatial pattern that describes the hotspots of Violent and Antisocial crime is defined as follows:

- Significant features (henceforth SF)
    - A:Sustenance, B:bus stop, C: alcohol amenity
- Correlation
    - C/A=0.8, C/B=0.38, B/A=2.17
- Distribution
    - Clustered

4 Conclusion

This paper presents a methodology of describing regions with significant high or low crime activity using spatial patterns. We investigate how the physical components, such as spatial features, and meta-data, such as population, can determine the crime rate. More specifically, we conduct statistical analysis on hot and cold crime spots, in order to formalize the composition of such places using spatial patterns. The proposed methodology is applied on antisocial and violent crime hotspots and resulted to a representative spatial pattern. The next stage of this work will focus on the inclusion of further explanatory features to better approximate spatial patterns for coldspots. Other interesting directions for future work include the utilization of the composition patterns in crime prediction and the extraction of the most prevalent crime indicators.

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